CLAIMS

What is claimed is:

1. An analysis system, comprising:

a control component that selectively gathers perception evidence to limit utilization of computing resources by a perception system; and

an analysis component that utilizes an analysis policy to analyze the perception evidence obtained for employment in the perception system; the analysis component is interactive with the control component for perception evidence analysis operations.

2. The system of claim 1, the analysis component employing, at least in part, learned inferences relating to persistence versus volatility of observational states to account for unobserved data.

3. The system of claim 2, the learned inferences based, at least in part, on a probability distribution over future states based on at least one previously observed value that is captured by at least one function of time.

4. The system of claim 3, the probability distribution comprising a Gaussian distribution:

$$P(x) = \frac{1}{(2\pi\sigma(t)^2)^{1/2}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma(t)^2}\right\}$$

where μ is a mean value and $\sigma(t)$ is a standard deviation at time "t."

5. The system of claim 1, the control component employing a criticality level of at least one user task to limit utilization of computing resources by the perception system.

6. The system of claim 1, the control component limiting utilization of computing resources based upon context.

7. The system of claim 1, the control component limiting utilization of computing resources by controlling what analysis policy is employed.

8. The system of claim 7, the selection of the analysis policy based on context information.

9. The system of claim 1, further comprising at least one perception sensor to provide the perception evidence for the perception system.

10. The system of claim 9, the control component limiting utilization of computing resources by facilitating control of at least one selected from the group consisting of an analysis process for at least one perception sensor and a focus of attention of at least one perception sensor.

11. The system of claim 9, the control component limiting utilization of computing resources by controlling what perception sensors are employed.

12. The system of claim 9, the perception sensor comprising at least one selected from the group consisting of a video camera, an audio microphone, a keyboard keystroke sensor, a mouse utilization sensor, and a motion detector.

13. The system of claim 9, the perception sensor comprising a detector for at least one state of at least one selected from the group consisting of at least one data structure within a computing system and at least one application activity within a computing system.

14. The system of claim 1, further comprising a user interface component that interfaces with at least one user to relay information relating to user perception preferences to the perception system.

15. The system of claim 14, the control component employing at least one user perception preference to limit utilization of computing resources by the perception system.

16. The system of claim 14, the user perception preferences comprising values of cost for utilizing computing resources.

17. The system of claim 1, the perception evidence analysis operations comprising analysis policy selection control operations between the control component and the analysis component.

18. The system of claim 1, the perception evidence analysis operations comprising perception evidence related information exchanges between the control component and the analysis component.

19. The analysis system of claim 1 utilized to design an analysis policy of at least one perception system and its perception sensors.

20. The analysis system of claim 1 utilized to determine at least one value of adding at least one sensor to at least one perception system.

21. The analysis system of claim 1 utilized to provide information relating to volatility of data due to influences of a flow of time.

22. The analysis system of claim 1 utilized to determine at least one time-based economic value of a business given its environmental context.

23. The system of claim 1, the analysis policy comprising a context-based analysis policy.

24. The system of claim 1, the analysis policy comprising a random selection perception policy that randomly selects which features to utilize on a frame by frame basis.

25. The system of claim 1, the analysis policy comprising a rate-based perception policy that defines observational frequencies and duty cycles for at least one feature.

26. The system of claim 25, the rate-based perception policy utilizing off-time that is determined by cross-validation means on a real-time data validation set to determine time for computations.

27. The system of claim 1, the analysis policy comprising an EVI-based perception policy that determines an expected value of information *via* a cost-benefit analysis means utilizing at least expected values and cost of analysis values for at least one feature.

28. The system of claim 27, the cost of analysis values comprising at least one value proportional to an impact to the computing resources employed by the perception system.

29. The system of claim 27, the EVI-based perception policy employing a context-based cost model to determine the cost of analysis values.

30. The system of claim 27, the EVI-based perception policy employing real-time computations of expected value of information.

31. The system of claim 30, the real-time computations processed utilizing a myopic, single step approach for computing a next best set of observations.

32. The system of claim 27, the cost of analysis values comprising at least one selected from the group consisting of dollar values, percentage of CPU utilization values, latency values, and user selected preference values.

33. The system of claim 27, the cost-benefit analysis means utilizing substantially similar value types for a cost value and a benefit value to calculate the expected value of information.

34. The system of claim 27, the cost-benefit analysis means further comprising at least one utility model that facilitates in analyzing a benefit of determining a value of at least one feature.

35. The system of claim 34, the utility model comprising a conditional utility model that alters functionality dependent upon context.

36. The system of claim 34, the expected value of information determined, at least in part, *via* utilization of Equation (2):

$$EVI(f_k) = EV(f_k) - \max_i \sum_j P(M_j \mid E) U(M_i, M_j) - cost(f_k) \qquad \text{Eq. (2)}$$

where $EVI(f_k)$ is the expected value of information for perceptual feature combination f_k, $EV(f_k)$ is an expected value of f_k based on observed evidence, E represents previous observational evidence, $U(M_i, M_j)$ is a utility of assessing a value of asserting that real-world state M_i is M_j, and $cost(f_k)$ is a computational cost associated with computing feature combination f_k.

37. The system of claim 27, the EVI-based perception policy further comprising a probabilistic model.

38. The system of claim 37, the probabilistic model comprising a Hidden Markov Model (HMM) model.

39. The system of claim 38, the expected value of information determined, at least in part, *via* Equation (4):

$$EVI(f_k) \propto \int \sum_n [\sum_s \alpha_t^n(s) \sum_l a_{sl}^n b_l^n (O_{t+1}^{f_k})] P(M_n)$$

$$\max_i \sum_j U(M_i, M_j) p(M_j) d_{O_{t+1}^{f_k}}$$

$$- \max_i \sum_j U(M_i, M_j) p(M_j) - cost(O_{t+1}^{f_k}) \qquad \text{Eq. (4)}$$

where $EVI(f_k)$ is the expected value of information for perceptual feature combination f_k, $\alpha_t^n(s)$ is an alpha or forward variable at time t and state s in a standard Baum-Welch algorithm, a_{sl}^n is a transition probability of going from state s to state l, and $b_l^n(O_{t+1}^{f_k^m})$ is a probability of observing $O_{t+1}^{f_k^m}$ in state l, all of them in model M_n, $U(M_i, M_j)$ is a utility of assessing a value of asserting that real-world state M_i is M_j, and f_k^m, $m = 1 \ldots M$ to denote all possible values of a feature combination f_k, and $cost(O_{t+1}^{f_k^m})$ is a computational cost associated with computing observations $O_{t+1}^{f_k^m}$.

40. The system of claim 38, the expected value of information determined, at least in part, *via* discretized Equation (5):

$$EVI \propto \sum_m \sum_n [\sum_s \alpha_t^n(s) \sum_l a_{sl}^n b_l^n(O_{t+1}^{f_k^m})] P(M_n) \max_i \sum_j U(M_i, M_j) p(M_j) - \max_i \sum_j U(M_i, M_j) p(M_j) - cost(O_{t+1}^{f_k}) \qquad \text{Eq. (5)}$$

where *EVI* is the expected value of information, $\alpha_t^n(s)$ is an alpha or forward variable at time *t* and state *s* in a standard Baum-Welch algorithm, a_{sl}^n is a transition probability of going from state *s* to state *l*, and $b_l^n(O_{t+1}^{f_k^m})$ is a probability of observing $O_{t+1}^{f_k^m}$ in state *l*, all of them in model M_n, $U(M_i, M_j)$ is a utility of assessing a value of asserting that real-world state M_i is M_j, and f_k^m, $m = 1 \ldots M$ to denote discretized values of a feature combination f_k, and $cost(O_{t+1}^{f_k^m})$ is a computational cost associated with computing observations $O_{t+1}^{f_k^m}$.

41. The system of claim 37, the probabilistic model comprising a Layered Hidden Markov Model (LHMM) model.

42. The system of claim 41, the Layered Hidden Markov Model (LHMM) utilized to substantially reduce re-training of higher level layers when an operating environment change occurs.

43. A method of analyzing data, comprising:

obtaining perception evidence for a perception system for a particular context;

analyzing the perception evidence utilizing an analysis policy to determine a perceived system value; and

employing the perceived system value to limit utilization of computing resources by the perception system.

44. The method of claim 43, analyzing the perception evidence further comprising:

employing, at least in part, learned inferences relating to persistence versus volatility of observational states to provide unobserved perception evidence in lieu of observed perception evidence.

45. The method of claim 44, the learned inferences based, at least in part, on a probability distribution model for future states based on at least one previously observed value that is captured by at least one function of time.

46. The method of claim 45, the probability distribution model comprising, at least in part, a Gaussian distribution:

$$P(x) = \frac{1}{(2\pi\sigma(t)^2)^{1/2}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma(t)^2}\right\}$$

where μ is a mean value and $\sigma(t)$ is a standard deviation at time "t."

47. The method of claim 43, further comprising:

accepting user input to obtain user preferences to establish criteria for limiting utilization of the computing resources by the perception system.

48. The method of claim 47, the criteria comprising at least one critical task that supersedes analysis of perception evidence for at least one feature in a given context.

49. The method of claim 43, further comprising:

employing at least one perception sensor to obtain the perception evidence; and

extracting perception evidence pertaining to at least one feature from the perception sensor.

50. The method of claim 49, further comprising:

selecting what perception sensors are employed to obtain perception evidence to further optimize the limiting of the computing resources employed by the perception system.

51. The method of claim 49, further comprising:

selecting when perception sensors are employed to obtain perception evidence to further optimize the limiting of the computing resources employed by the perception system.

52. The method of claim 49, at least one perception sensor comprising perception evidence for at least one feature.

53. The method of claim 43, further comprising:

selecting the analysis policy based on optimization of limiting computing resources for a given context.

54. The method of claim 43, further comprising:

selecting the analysis policy based on optimization of limiting computing resources for obtaining a desired feature.

55. The method of claim 43, employing the perceived system value comprising utilizing computing resources when the perceived system value is above a threshold.

56. The method of claim 43, employing the perceived system value comprising utilizing computing resources for a feature combination that yields a maximal perceived system value.

57. The method of claim 55, the threshold is a predetermined threshold.

58. The method of claim 57, the predetermined threshold is set *via* a user preference.

59. The method of claim 57, the predetermined threshold is set *via* the perception system based on context.

60. The method of claim 43, the analysis policy comprising a rate-based perception policy.

61. The method of claim 60, further comprising:

defining observational frequencies and duty cycles *via* a cross-validation means on a real-time data validation set for perception sensors employed by the perception system; and

determining which perception sensors are providing sensed data and utilizing the sensed data to compute features facilitated by the sensed data.

62. The method of claim 61, further comprising:

adapting the observational frequencies and duty cycles for at least one sensor dynamically.

63. The method of claim 43, the analysis policy comprising a random selection-based perception policy.

64. The method of claim 63, further comprising:

determining features available based on available perception sensors employed by the perception system;

randomly selecting which features to analyze; and

processing at least one analyzed feature to determine output perception data.

65. The method of claim 43, the analysis policy comprising an EVI-based perception policy.

66. The method of claim 65, further comprising:

calculating a benefit value for determining a feature;

calculating a cost value for determining the feature; and

utilizing the EVI-based perception policy to derive a cost-benefit analysis value of the feature; the cost benefit analysis utilizing a benefit value and a cost value.

67. The method of claim 66, the benefit value and the cost value calculated employing a substantially similar value type.

68. The method of claim 67, the value type comprising at least one selected from the group consisting of a dollar value, a percentage of CPU utilization value, a latency value, and a user-selected value.

69. The method of claim 65, the EVI-based perception policy further comprising at least one selected from the group consisting of a utility model and a probabilistic model.

70. The method of claim 69, further comprising:

evaluating an expected value of information (EVI) utilizing, at least in part, employment of Equation (2):

$$EVI(f_k) = EV(f_k) - \max_i \sum_j P(M_j \mid E) U(M_i, M_j) - cost(f_k) \quad \text{Eq. (2)}$$

where $EVI(f_k)$ is the expected value of information for perceptual feature combination f_k, $EV(f_k)$ is an expected value of f_k based on observed evidence, E represents previous observational evidence, $U(M_i, M_j)$ is a utility of assessing a value of asserting that real-

world state M_i is M_j, and $cost(f_k)$ is a computational cost associated with computing feature combination f_k.

71. The method of claim 69, the probabilistic model comprising a Hidden Markov Model (HMM).

72. The method of claim 71, further comprising:

evaluating an expected value of information (EVI) utilizing, at least in part, employment of Equation (4):

$$EVI(f_k) \propto \int \sum_n [\sum_s \alpha_t^n(s) \sum_l a_{sl}^n b_l^n(O_{t+1}^{f_k})] P(M_n)$$

$$\max_i \sum_j U(M_i, M_j) p(M_j) d_{O_{t+1}^{f_k}}$$

$$- \max_i \sum_j U(M_i, M_j) p(M_j) - cost(O_{t+1}^{f_k}) \qquad \text{Eq. (4)}$$

where $EVI(f_k)$ is the expected value of information for perceptual feature combination f_k, $\alpha_t^n(s)$ is an alpha or forward variable at time t and state s in a standard Baum-Welch algorithm, a_{sl}^n is a transition probability of going from state s to state l, and $b_l^n(O_{t+1}^{f_k^m})$ is a probability of observing $O_{t+1}^{f_k^m}$ in state l, all of them in model M_n, $U(M_i, M_j)$ is a utility of assessing a value of asserting that real-world state M_i is M_j, and f_k^m, $m = 1 \ldots M$ to denote all possible values of a feature combination f_k, and $cost(O_{t+1}^{f_k^m})$ is a computational cost associated with computing observations $O_{t+1}^{f_k^m}$.

73. The method of claim 71, further comprising:

evaluating an expected value of information (EVI) utilizing, at least in part, employment of discretized Equation (5):

$$EVI \propto \sum_m \sum_n [\sum_s \alpha_t^n(s) \sum_l a_{sl}^n b_l^n (O_{t+1}^{f_k^m})] P(M_n) \max_i \sum_j U(M_i, M_j) p(M_j) - \max_i \sum_j U(M_i, M_j) p(M_j) - cost(O_{t+1}^{f_k}) \qquad \text{Eq. (5)}$$

where *EVI* is the expected value of information, $\alpha_t^n(s)$ is an alpha or forward variable at time t and state s in a standard Baum-Welch algorithm, a_{sl}^n is a transition probability of going from state s to state l, and $b_l^n(O_{t+1}^{f_k^m})$ is a probability of observing $O_{t+1}^{f_k^m}$ in state l, all of them in model M_n, $U(M_i, M_j)$ is a utility of assessing a value of asserting that real-world state M_i is M_j, and f_k^m, $m = 1 \ldots M$ to denote discretized values of a feature combination f_k, and $cost(O_{t+1}^{f_k^m})$ is a computational cost associated with computing observations $O_{t+1}^{f_k^m}$.

74. The method of claim 69, the probabilistic model comprising a Layered Hidden Markov Model (LHMM).

75. The method of claim 74, further comprising:

employing lower level layers of the LHMM to mask higher level layers from needing to be re-trained when the perception system is changed to a new environment.

76. A perception evaluation system utilizing the method of claim 43 to determine benefits of additional perception sensors to a perception system.

77. A perception design system utilizing the method of claim 43 to design a perception system to optimally limit utilization of computing resources.

78. A perception response system employing the method of claim 43 to provide information utilizing knowledge of volatility of data due to influences of a flow of time to re-determine perceptions at appropriate intervals.

79. A data analysis system, comprising:

means to selectively gather perception evidence obtained for employment *via* a perception system to limit utilization of computing resources by the perception system; and

means to analyze the perception evidence utilizing an analysis policy employed to facilitate in limiting utilization of the computing resources.

80. A data analysis system, comprising:

a first component that receives data queries relating to obtained data; and

a second component that analyzes persistence of at least one state of obtained data with regard to volatility of the data over time to establish reasonableness in timing of at least one query reply.

81. A data packet transmitted between two or more computer components that facilitate perception, the data packet is comprised of, at least in part, information relating to a system that determines, based, at least in part, on expected value of information, employed to facilitate limiting utilization of computational resources.

82. A computer readable medium having stored thereon computer executable components of the system of claim 1.

83. A device employing the method of claim 43 comprising at least one selected from the group consisting of a computer, a server, and a handheld electronic device.

84. A device employing the system of claim 1 comprising at least one selected from the group consisting of a computer, a server, and a handheld electronic device.